Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA

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ABSTRACT

Multispectral satellite data have become a common tool used in the mapping of wildland fire effects. Fire severity, defined as the degree to which a site has been altered, is often the variable mapped. The Normalized Burn Ratio (NBR) used in an absolute difference change detection protocol (dNBR), has become the remote sensing method of choice for US Federal land management agencies to map fire severity due to wildland fire. However, absolute differenced vegetation indices are correlated to the pre-fire chlorophyll content of the vegetation occurring within the fire perimeter. Normalizing dNBR to produce a relativized dNBR (RdNBR) removes the biasing effect of the pre-fire condition. Employing RdNBR hypothetically allows creating categorical classifications using the same thresholds for fires occurring in similar vegetation types without acquiring additional calibration field data on each fire. In this paper we tested this hypothesis by developing thresholds on random training datasets, and then comparing accuracies for (1) fires that occurred within the same geographic region as the training dataset and in similar vegetation, and (2) fires from a different geographic region that is climatically and floristically similar to the training dataset region but supports more complex vegetation structure. We additionally compared map accuracies for three measures of fire severity: the composite burn index (CBI), percent change in tree canopy cover, and percent change in tree basal area. User's and producer's accuracies were highest for the most severe categories, ranging from 70.7% to 89.1%. Accuracies of the moderate fire severity category for measures describing effects only to trees (percent change in canopy cover and basal area) indicated that the classifications were generally not much better than random. Accuracies of the moderate category for the CBI classifications were somewhat better, averaging in the 50%–60% range. These results underscore the difficulty in isolating fire effects to individual vegetation strata when fire effects are mixed. We conclude that the models presented here and in Miller and Thode ([Miller, J.D. & Thode, A.E., (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). Remote Sensing of Environment, 109, 66–80.]) can produce fire severity classifications (using either CBI, or percent change in canopy cover or basal area) that are of similar accuracy in fires not used in the original calibration process, at least in conifer dominated vegetation types in Mediterranean–climate California.

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1. Introduction

Multispectral satellite data have become a common tool in the mapping of wildland fire effects (Tanaka et al., 1983; Lopez Garcia & Caselles, 1991; Rogan & Franklin, 2001; Miller & Yool, 2002; Brewer et al., 2005; Wimberly & Reilly, 2007). "Fire severity" is one of the most commonly mapped measures of fire effects to vegetation and soils (Ryan & Noste, 1983; Agee, 1993; DeBano et al., 1998; Lentile et al., 2006). In the disturbance ecology literature, "severity" is usually defined as the effect of a change agent on an ecological community, or a measure of the degree to which a site has been altered (Pickett & White, 1985; Turner et al., 1998). The composite burn index (CBI) was developed by Key and Benson (2005a) as a semi-quantitative field measure of fire severity experienced in a plot, and has recently been

used in several fire severity mapping studies (van Wagtendonk et al., 2004; Epting et al., 2005; De Santis & Chuvieco, 2007). CBI is normally calculated as the linear average of fire effects seen in all vegetation strata (i.e., understory, midstory and overstory), exposed surface soil, and non-photosynthetic surface fuels. CBI should therefore be correlated to satellite derived indices since satellites provide integrated measurements at the pixel level (Key, 2006). Chuvieco et al. (2006) have shown that CBI is highly correlated to the Landsat near infrared (NIR) band in combination with either the red or short wave infrared (SWIR) bands.

While CBI field values can be calculated for an individual stratum, i.e. the upper canopy, or as an average across all strata, CBI is not a variable that is familiar to most resource managers. In forested environments, Landsat derived indices are predominantly correlated to variables describing the upper canopy structure (Stenback & Congalton, 1990; Cohen & Spies, 1992; Zhu et al., 2006; De Santis & Chuvieco, 2007). Landsat-derived indices of fire effects to forestlands should therefore theoretically be correlated to pre- and post-fire measures of basal area and canopy cover, which are commonly used field measures of upper forest canopy structure (Cade, 1997). Basal area, defined as the sum of the cross-sectional areas of tree boles in a sampled area, forms the fundamental basis for mensuration, analysis, mapping and management of forest resources (USDA, 1992; Avery & Burkhart, 1994). Canopy cover, defined as "the proportion of ground… expressed as a percentage that is occupied by the perpendicular projection downward of the aerial parts of the vegetation" is an important variable most often used in models of wildlife and plant species habitat (Cade, 1997; Brohman & Bryant, 2005; Zielinski et al., 2006). Habitat maps are often made, and habitat models calibrated, from aerial photography where canopy cover can be the only practicable measure of tree cover (Cade, 1997). Moreover, basal area and canopy cover can be derived from Forest Inventory and Analysis (FIA) plot data that form the backbone of forest inventory data on USDA Forest Service lands (USDA, 1992; Dixon, 2002). The FIA program does not explicitly measure canopy cover; it must be modeled using tree inventories by species and diameter. In order to meet the needs of silviculturists and biologists, severity maps in both units of canopy cover and basal area are often desirable.

The Normalized Burn Ratio (NBR) computed from Landsat TM NIR and SWIR bands (4 and 7, respectively) has gained considerable attention in recent years for mapping burned areas (Miller & Yool, 2002; Brewer et al., 2005; Epting et al., 2005; Key & Benson, 2005b). NBR is formulated like the normalized difference vegetation index (NDVI) except Landsat TM SWIR band 7 is used in place of the red band 3 as follows:

$$NBR = \frac{Band4 - Band7}{Band4 + Band7}.$$ (1)

NBR is primarily sensitive to living chlorophyll and water content of soils and vegetation, but it is also responsive to lignin, hydrous minerals, ash and char (Elvidge, 1990; Key, 2006; Kokaly et al., 2007). Most fire severity mapping applications to date have subtracted a post-fire NBR image from a pre-fire NBR image in an absolute change detection methodology to derive the "differenced NBR" (dNBR) as follows:

$$dNBR = prefireNBR - postfireNBR.$$ (2)

Since chlorophyll contents vary due to vegetation type and density, each absolute differenced image should ideally be stratified by pre-fire vegetation type and independently calibrated (Miller & Yool, 2002; Key & Benson, 2005b; Zhu et al., 2006; Kokaly et al., 2007; Miller & Thode, 2007). Miller and Thode (2007) therefore proposed the creation of a relative differenced NBR (RdNBR) to remove the biasing

of the pre-fire vegetation by dividing dNBR by the square-root of the pre-fire NBR as follows:

$$RdNBR = \frac{dNBR}{\sqrt{ABS(prefireNBR/1000)}}.$$ (3)

By convention, NBR is scaled by 1000 to transform the data to integer format; therefore the pre-fire NBR must be divided by 1000 in the RdNBR formula (Key, 2006; Miller & Thode, 2007). The absolute value of the pre-fire NBR in the denominator allows computing the square-root without changing the sign of the original dNBR. Positive RdNBR values therefore represent a decrease in vegetation cover, just like dNBR, while negative values represent an increase in vegetation cover. Ideally, normalization should not require applying a square-root transformation to the denominator, but Miller and Thode (2007) found that the square-root allowed a better fit of a relative dNBR index to field values in sparsely vegetated plots.

Ecological studies have long used either or both absolute and relative versions of the same measure (i.e. density, frequency, and dominance) depending on the definition of the measure being addressed (McCune & Grace, 2002). Both absolute and relative measures are useful and provide different information about fire effects, e.g. the amount of biomass killed vs. the percentage of biomass killed. It should be noted that most variables included in the CBI protocol are estimated from the relative change perspective (Key & Benson, 2005a). Hypothetically, a major advantage of relative indices is that a single set of thresholds can be used to create categorical severity classifications for fires occurring in similar vegetation types without requiring additional calibration field data for each fire (Zhu et al., 2006; Miller & Thode, 2007). This paper tests this hypothesis by using thresholds developed on a randomly selected training dataset to assess classification accuracy on independently mapped fires. Map accuracies were compared for: 1) fires that occurred within the same geographic region as the training dataset and in similar vegetation types, and 2) fires from a different geographic region that is climatically and floristically similar to the training dataset region but supported more complex vegetation structure. Additionally, three different measures of fire severity based on CBI, percent change in canopy cover, and percent change in basal area were calibrated to RdNBR and their accuracies assessed.

Miller and Thode (2007) presented a classification derived from a regression of CBI to RdNBR using all plots regardless of vegetation type, including non-forested types, and without withholding an independent set of plots for validation. However, high-quality accuracy assessment procedures require that validation data be independent of the training data so that the assessment is not biased in favor of the map (Congalton & Green, 1999). We therefore also compared a classification of plots randomly selected from the same fires used for training to the original classification reported in Miller and Thode (2007) to assess whether using all plots affected classification accuracies.

2. Data and methods

2.1. Study locations

2.1.1. Sierra Nevada

Twenty-five fires used in this study are located within the region formed by the Sierra Nevada Forest Plan Amendment (SNFPA) planning area (USDA, 2004), which guides land and resource management on 50,000 km^2 of National Forest land on eleven US National Forests (Fig. 1 and Table 1). CBI data from fourteen of these fires that occurred in 2002–2004 were originally used by Miller and Thode (2007). Four additional fires that occurred in 2001 along with seven fires that occurred entirely within Yosemite National Park (NP) were included in this study. Yosemite NP is not managed under the
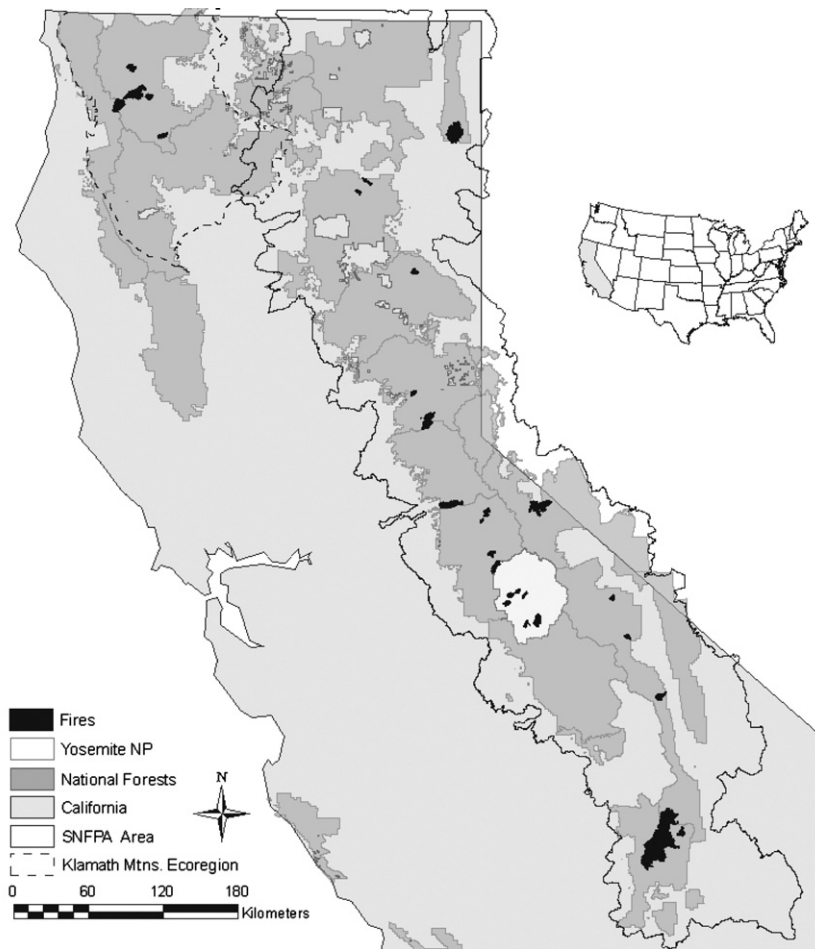
Fig. 1. Map of the study area showing location of the fires used in the analyses.

SNFPA but is nested within the SNFPA area (further references to the "SNFPA area" should be understood to exclude Yosemite NP). The SNFPA planning area not only includes the Sierra Nevada and its foothills but also the Warner Mountains, Modoc Plateau, White Mountains, Inyo Mountains and portions of the southern Cascades. Climate is Mediterranean-type, with warm, dry summers and cool, wet winters; nearly all precipitation falls between October and April (Minnich, 2007). Forest vegetation in the SNFPA areas sampled in this study is very diverse, with different dominant species and high variation in density and vertical structure. Most fires (and the majority of sample plots) were located in montane vegetation types, with ponderosa pine (*Pinus ponderosa*) dominant at lower elevations; white fir (*Abies concolor*), incense cedar (*Calocedrus decurrens*), sugar pine (*P. lambertiana*), ponderosa pine, and Douglas fir (*Pseudotsuga menziesii*) at intermediate elevations; and Jeffrey pine (*P. jeffreyi*) and red fir (*A. magnifica*) at the higher elevations. The amount of understory in the montane forest zone is variable and largely dependent on the openness of the forest. In the absence of periodic fires, dense thickets of conifer seedlings and saplings have become common (Kilgore & Taylor, 1979; Parsons & DeBenedetti, 1979). Shrubs are patchy with variable abundance (cover typically 5–10%, but can be >30%); herbs and grasses are sparse, with cover usually <5% (Rundel et al., 1977). Fires east of the Sierra Nevada crest and in the Cascade Range were generally located in ponderosa pine forest with an understory of grasses and Great Basin shrub species, such as sagebrush (*Artemisia tridentata*) and bitterbrush (*Purshia tridentata*). Juniper (*Juniperus occidentalis*) is common in more xeric east-side sites. Elevations of plots within fire perimeters ranged from 1375 to 2903 m.

2.1.2. Klamath Mountains

Five fires in this study occurred during 2006 on the Klamath and Six Rivers National Forests in the Klamath Mountains of northwestern California (Fig. 1 and Table 1). Climate in the Klamath Mountains is also Mediterranean, but can be variable due to strong west to east moisture and temperature gradients caused by steep, complex terrain and proximity to the Pacific Ocean (Skinner et al., 2006). While most of the dominant conifer species are shared with the Sierra Nevada and Cascade Ranges, overall conifer diversity is much higher in the Klamaths, and forest environments are generally more mesic with correspondingly greater vegetation diversity and complexity (Barbour et al., 2007). Midstory evergreen and deciduous hardwood trees are abundant, often forming a multistoried canopy, and a cover of herbaceous understory vegetation can be substantial (Sawyer & Thornburgh, 1977; Sawyer et al., 1977). Elevations of sample plots within fires in the Klamath Mountains ranged from 241–2084 m.

2.2. Field data

Field data were collected during the summer following each fire. Fires on National Forest lands were sampled by Forest Service crews, while National Park Service (NPS) or US Geological Survey (USGS) crews collected data on the fires that occurred in Yosemite NP. CBI data and/or individual tree mortality data were collected on all fires, but both protocols were not used on all fires (Table 1). Although the CBI protocol does call for estimating tree cover by stratum, i.e. sub-canopy and upper canopy, total tree canopy cover is not estimated so we were unable to include the Yosemite data in analyses stratified by pre-fire tree canopy cover.

Table 1
Fires included in the study

Year of fire	Fire name	[a]Unit	Path/row	Pre-fire image date	Post-fire image date	Train/validation	Field protocol
1999	Dark	Yosemite NP	42/34	7/9/1999	7/11/2000	V	CBI
1999	Lost Bear	Yosemite NP	42/34	7/9/1999	7/11/2000	V	CBI
2001	Blue	Modoc NF	44/31	7/28/2001	7/15/2002	V	Tree mortality
2001	Gap	Tahoe NF	43/33	8/6/2001	7/8/2002	V	Tree mortality
2001	Hoover	Yosemite NP	42/34	7/27/2000	8/2/2002	V	CBI
2001	Star	Eldorado NF	43/33	8/6/2001	7/8/2002	V	Tree mortality
2001	Stream	Plumas NF	44/32	7/12/2001	6/29/2002	V	Tree mortality
2002	Birch	Inyo NF	42/34	6/7/2002	6/10/2003	T&V	Tree mortality, CBI
2002	Cannon	Humbolt–Toiyabe NF	43/33	6/14/2002	7/3/2003	T&V	Tree mortality, CBI
2002	Cone	Lassen NF	44/32	9/25/2002	9/12/2003	T&V	Tree mortality, CBI
2002	Fuller	Inyo NF	42/34	7/9/2002	7/12/2003	T&V	Tree mortality, CBI
2002	McNally	Sequoia NF	41/35	6/16/2002	6/19/2003	T&V	Tree mortality, CBI
2002	PW-3	Yosemite NP	42/34	7/9/2002	7/12/2003	V	CBI
2002	Wolf	Yosemite NP	42/34	7/9/2002	7/12/2003	V	CBI
2003	Albanita	Sequoia NF	41/35	8/22/2003	8/8/2004	T&V	Tree mortality, CBI
2003	Dexter	Inyo NF	42/34	7/12/2003	7/30/2004	T&V	Tree mortality, CBI
2003	Hooker	Sequoia NF	41/35	8/22/2003	8/8/2004	T&V	Tree mortality, CBI
2003	Kibbie	Stanislaus NF	42/34	7/12/2003	7/30/2004	T&V	Tree mortality, CBI
2003	Mountain Cmplx	Stanislaus NF	43/33	7/3/2003	7/5/2004	T&V	Tree mortality, CBI
2003	Mud	Stanislaus NF	43/33	7/3/2003	7/5/2004	T&V	Tree mortality, CBI
2003	Tuolomne	Yosemite NP	42/34	7/12/2003	7/14/2004	V	CBI
2003	Whiskey	Yosemite NP	42/34	7/12/2003	7/14/2004	V	CBI
2003	Whit	Stanislaus NF	43/33	7/3/2003	7/5/2004	T&V	Tree mortality, CBI
2004	Power	Eldorado NF	43/33	7/5/2004	8/25/2005	T&V	Tree mortality, CBI
2004	Straylor	Lassen NF	44/32	9/12/2003	9/1/2005	T&V	Tree mortality, CBI
2006	Hancock	Klamath NF	46/31	8/23/2005	8/13/2007	V	Tree mortality, CBI
2006	Rush	Klamath NF	46/31	8/23/2005	8/13/2007	V	Tree mortality, CBI
2006	Somes	Six Rivers NF	46/31	8/23/2005	8/13/2007	V	Tree mortality, CBI
2006	Titus	Klamath NF	46/31	8/23/2005	8/13/2007	V	Tree mortality, CBI
2006	Uncles	Klamath NF	46/31	8/23/2005	8/13/2007	V	Tree mortality, CBI

[a] SNFPA area fires included all units except Yosemite NP and Klamath NF.

When performing accuracy assessments, plots should ideally be randomly located. In this way the distribution of field reference plots will match the distribution of the features being mapped. If plots are preferentially located in a map category that yields a higher accuracy than another category, then map accuracy will be biased and artificially inflated (Stehman & Czaplewski, 1998; Congalton & Green, 1999). Plots sampled in the SNFPA planning area were located at least 300 m apart on randomly placed transects. Fig. 2 shows that plots measured in the SNFPA fires provide a more or less unbiased sample of the background distribution of RdNBR values in forest vegetation types as delineated by the latest vegetation map used by the Forest Service (Franklin et al., 2000; USDA, 2007). A stratified random procedure was used to generate potential plot locations on the 2006 fires in the Klamath Mountains using a preliminary severity map. Plot locations were chosen to be within one day's hike of a road, because much of the burned area occurred in remote or wilderness areas with difficult access. In selecting plots we emphasized those that exhibited fire effects in the upper-moderate and lower-high severity categories. Since managers have the most interest in identifying landscapes that experienced the greatest change with fire, we wanted to evaluate whether our mapping methods would correctly classify those locations. Plot locations in the Yosemite fires were selected randomly within a stratification based on vegetation type.

2.2.1. CBI

The CBI protocol (Key & Benson, 2005a) records fire effects derived from ocular estimates in five vertical strata: 1) surface fuels and soils; 2) herbs, low shrubs and trees less than 1 m tall; 3) shrubs and trees 1 to 5 m tall; 4) intermediate trees; and 5) large trees. Four or five variables describing specific effects in each stratum were visually estimated and scored with a value between zero and three, with zero indicating no effect of the fire (i.e. unburned) and a three being maximum severity. As an enhancement to the CBI protocol, actual values were estimated and recorded for each variable on the SNFPA fires that occurred during 2004 and the 2006 fires in the Klamath Mountains. For example, the actual estimated percent canopy

mortality (0–100%) was recorded in addition to rating canopy mortality with a value between zero and three. Total CBI values were derived by summing scores from all variables measured in each stratum and dividing by the number of values measured as described by Key and Benson (2005a).

Choosing which CBI values to use as thresholds between severity categories is somewhat subjective. Following Miller and Thode (2007), we chose to place the thresholds halfway between the values listed as general guides on the CBI data form for low, moderate and high categories (Table 2). For example, the CBI data form indicates "moderate" severity for the CBI columns 1.5 and 2.0, and "high" severity for 2.5 and 3.0. We therefore chose 2.25 as the threshold between "moderate" and "high" severity categories.

The same plot size was not used on all fires. The 30 m diameter plot size recommended by Key and Benson (2005a) was used on the fires that occurred in Yosemite NP and in the Klamath Mountains. Plots were either 60 m or 90 m diameter on the remaining fires (90 m in 2002–2004, and 60 m in 2005). With the exception of the Yosemite NP fires, we also documented the overall condition of each plot with photographs taken at all cardinal directions from the plot center.

The CBI protocol provides a consistent methodology for experienced users to quickly assess relative severity at a location, allowing a larger number of locations to be sampled than would be possible with a more quantitative protocol. However, variability in CBI values can occur since the measurements are ocular estimates and accuracy depends on observer expertise. Korhonen et al. (2006) found that mean ocular estimates of canopy cover made by experienced forestry personnel can disagree up to 16% (standard deviation=10%) from instrumented measurements. In this study, estimation error was probably exacerbated because the data were collected by different organizations and crew membership varied from year to year.

2.2.2. Tree mortality data

Data collected to characterize fire effects on trees included status (live or dead), species, diameter at breast height (dbh), tree height, scorch height, height to live crown (i.e. crown base height (CBH)), and
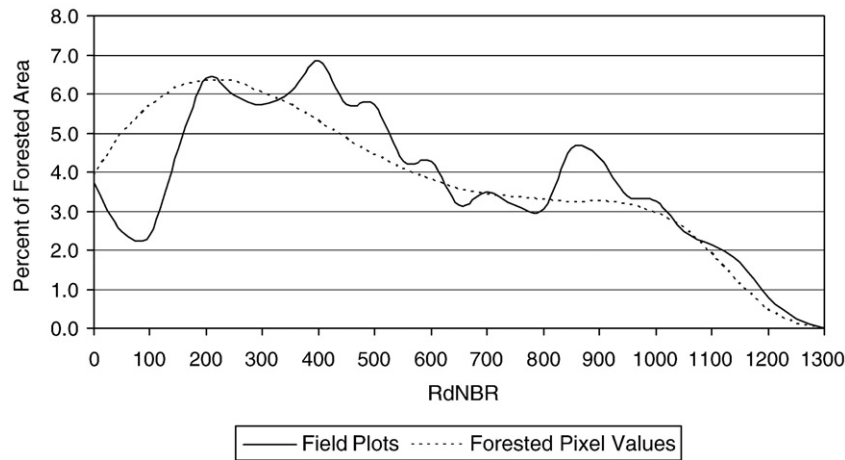
Fig. 2. Distribution of plot RdNBR values sampled in the SNFPA area fires vs. the distribution of all RdNBR pixel values in forested vegetation types.

percent of crown volume scorched. For fires that occurred in the Klamath Mountains, dbh was measured on each tree in the 30 m diameter plot. The numbers of trees less than 10 cm in diameter (saplings) were counted by species. Tree height and CBH measurements were made on the three trees within each plot exhibiting the maximum, minimum, and median scorch heights. For SNFPA fires where 60 and 90 m diameter plots were used, individual tree status and species were measured in four 10 m diameter subplots and tallied in 10 cm size classes. Whether dead trees were killed by the fire or were already dead prior to the fire was determined by presence or absence of dead needles as well as bark and wood consumption patterns.

Pre- and post-fire basal area was calculated from the diameters of trees thought to have been alive prior to the fire and alive after the fire. Pre- and post-fire canopy cover was estimated using the Forest Vegetation Simulator (FVS) (Dixon, 2002). FVS uses empirically derived allometric equations parameterized by species and dbh to model individual tree canopies. There are FVS variants for different geographic regions of the U.S. to account for regional differences in tree morphology. We used the northern California (NC) and western Sierra (WS) variants depending on fire location. FVS was configured to use random placement of trees and estimates of percent canopy cover were corrected for tree canopy overlap (Crookston & Stage, 1999). We did not attempt to evaluate how random placement of trees affected the accuracy of canopy cover estimates, but other researchers have found that FVS calculated canopy cover can be more variable than field based measurements, and that FVS may underestimate cover for plots with highly regular spatial patterns and overestimate cover for plots with clustered patterns (Fiala et al., 2006; Christopher & Goodburn, 2008).

FVS derived estimates of individual tree crown cover assume trees are healthy and unaffected by fire or disease. However, fire can modify dbh to canopy architecture relationships by raising CBH; thereby reducing canopy width. Since there was no way to modify crown width inside FVS, we derived a crown cover correction factor as a function of the percentage of crown volume scorched (PCVS). Equations for the Klamath variant of FVS (NC) were used to estimate an average tree height and crown width for all trees measured in the Klamath fires. We used equations for modeling crown shape for

northern California conifer species from Biging and Wensel (1990) to derive the percent crown cover reduction factor (PctCCF) as a function of PCVS (Fig. 3) as follows:

$$PCVS = \frac{V(h) \times 100}{CV} \tag{4}$$

$$PctCCF = \left(1 - \frac{PCVS}{100}\right) \times \left(\frac{H-CBH}{H-h}\right) \tag{5}$$

where CV is the total cubic crown volume computed using equation 1 from Biging and Wensel (1990); $V(h)$ is the cumulative crown volume from the pre-fire CBH to a height h computed using equation 2 from Biging and Wensel (1990); and H is the total tree height.

2.3. Imagery and preprocessing

Georegistration of images as well as environmental factors such as atmospheric conditions, topography, surface moisture, seasonal phenology, and solar zenith angle can influence analysis of multi-temporal change detection protocols (Singh, 1989; Coppin & Bauer, 1996). All images used in this project were acquired by Landsat TM or ETM+ sensors and geometrically registered using terrain correction algorithms (Level 1T) by the EROS Data Center and then converted to at sensor
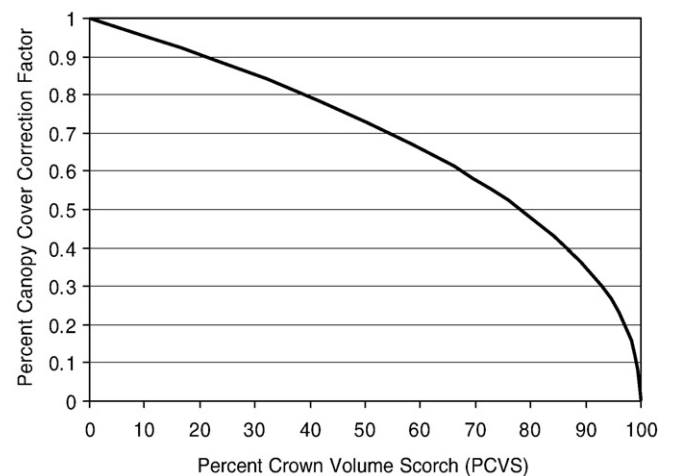
Table 2
CBI categories and threshold values

Severity category	CBI threshold
Unchanged to low	0–1.25
Moderate	1.26–2.25
High	2.26–3.0

Fig. 3. Canopy cover correction factor as a function of percent of crown volume scorched (PCVS). Function was derived from canopy models of conifers in northern California (Biging & Wensel, 1990).
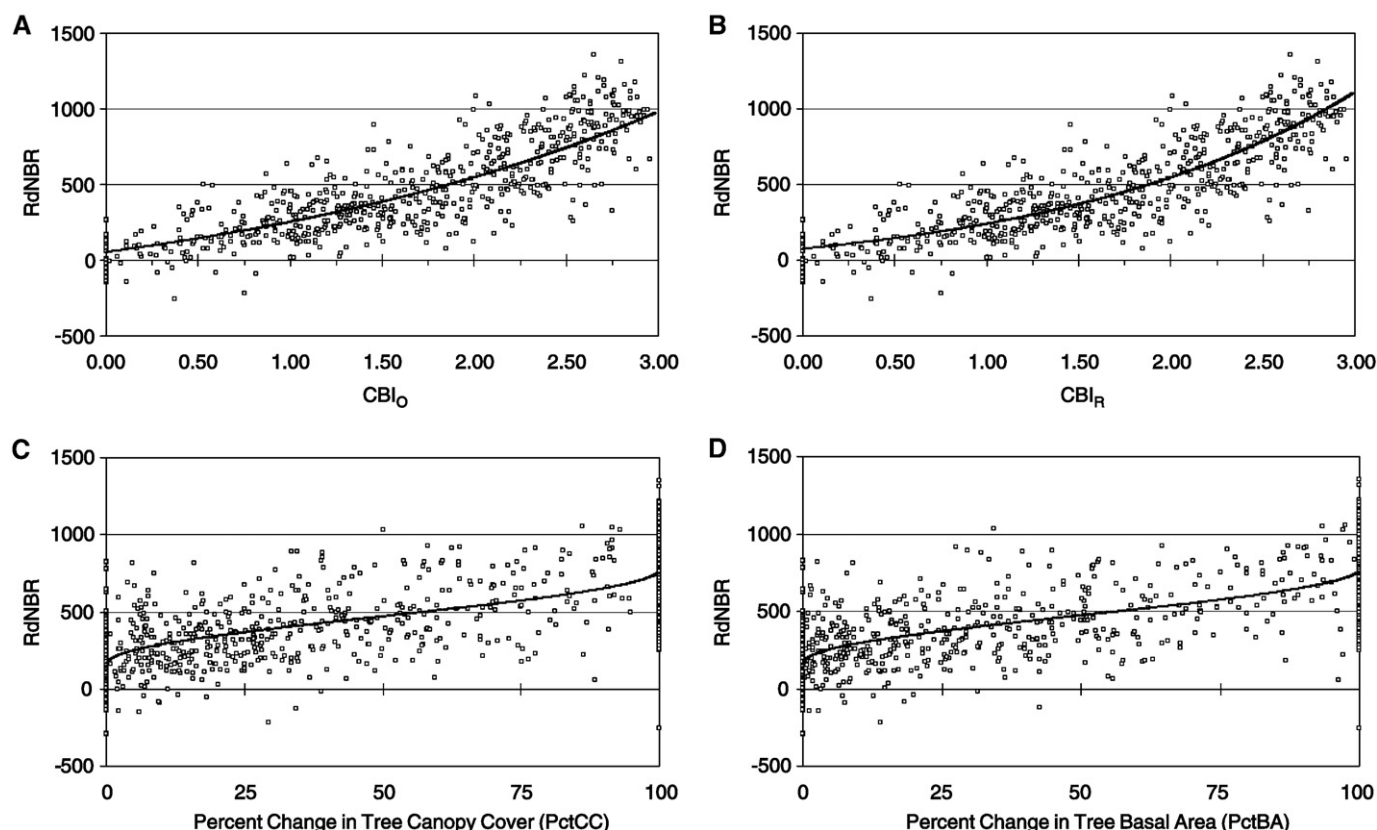
Fig. 4. Regression models overlain on RdNBR plot values for all plots with > 10% pre-fire tree cover in the SNFPA area (A) CBI modeled using all plots regardless of vegetation type, from Miller and Thode (2007), (B) CBI modeled using a random set of plots, (C) Percent change in tree canopy cover modeled using a random set of plots, (D) Percent change in tree basal area modeled using a random set of plots.

reflectance (NASA, 1998; Chander & Markham, 2003). Post-fire images were acquired during the summer of the year following each fire to match the date of field sampling (Table 1). Pre- and post-fire image pairs were matched as close as possible by anniversary date, within the constraints of limited budgets and availability of cloud-free imagery, to minimize sun angle effects and differences in phenology. We chose not to apply any atmospheric scattering algorithms because: 1) the NBR index employs only near and short-wave infrared wavelengths that are minimally affected by atmospheric scattering (Avery & Berlin, 1992), especially during the summer months in our study areas which have a Mediterranean climate; and 2) some of the most commonly applied atmospheric correction methods can produce higher error values across multiple dates than correction only to reflectance at the sensor (Schroeder et al., 2006). Satellite values were not corrected for topographic shading since NBR is a ratio and topographic effects cancel when atmospheric scattering is minimal and solar illumination is adequate (Kowalik et al., 1983; Ekstrand, 1996). NBR values were multiplied by 1000 and converted to integer format to match procedures established by Key and Benson (2005b).

RdNBR values were normalized in two ways: 1) before calculating RdNBR, dNBR values for each fire were normalized by subtracting the average dNBR value sampled from unburned areas outside the fire perimeter to account for inter-annual differences in phenology and ensure that unburned areas have values around zero (Key, 2006); 2) RdNBR was computed as a ratio of change in reflectance in relation to pre-fire reflectance values which normalized the index to account for variation in pre-fire vegetation type and density. Pixel values were thereby converted to a ratio, which theoretically ranges between zero for unburned areas to a maximum value that represents total above ground vegetation mortality. This should allow for the development of thresholds from one set of fires to be applied to other fires across time and space (Miller & Thode, 2007). In practice, RdNBR continues to vary

in value where complete vegetation mortality has occurred since NBR is sensitive to ash, char, and substrate composition (Kokaly et al., 2007).

2.4. Classifications

We divided plots from the fourteen 2002–2004 fires in the SNFPA area originally used in Miller and Thode (2007) into randomly selected training and validation sets (Table 1). The random training set was used to develop new regression models and classification thresholds. We constrained the training plots with the condition that they have at least 5% pre-fire tree canopy cover. For the remainder of this paper we refer to the classification originally reported in Miller and Thode (2007) as CBI_O and the classification developed using the random training set as CBI_R. We also developed regression models of percent change in tree canopy cover (PctCC) and basal area (PctBA) to RdNBR with data from the same random set of plots from 2002–2004 SNFPA area fires used to develop CBI_R.

Table 3
Regression models used to calibrate RdNBR to field measured fire severity measures

Variable	Model	R^2	P	Parameter (±Std. Error)		
				a	b	c
CBI_O	RdNBR = $a+b*$EXP(CBI$*c$)	0.61	<0.0001	−369.0 ±165.9	421.7 ±146.7	0.389 ±0.081
CBI_R	RdNBR = $a+b*$EXP(CBI$*c$)	0.68	<0.0001	−123.3 ±102.0	196.8 ±76.8	0.612 ±0.113
PctCC	RdNBR = $a+b*$ASIN(SQRT (PctCC/100))	0.52	<0.0001	161.0 ±19.5	392.6 ±21.4	
PctBA	RdNBR = $a+b*$ASIN(SQRT (PctBA/100))	0.53	<0.0001	166.5 ±19.0	389.0 ±20.9	

CBI_O, CBI_R, PctCC, and PctBA are described in the text.

2.5. Error analysis

Error matrices were calculated for classifications of all training and validation datasets. Only plots with at least 10% pre-fire tree canopy cover were included when computing error matrices since this is the cut-off the U.S. Forest Service uses for forested vegetation types (Brohman & Bryant, 2005). Yosemite plots were not restricted by pre-fire canopy cover because individual tree data were not available, and we were thus unable to calculate pre-fire total tree canopy cover. To conserve space, we report only producer's and user's accuracies and the Kappa statistic to describe overall classification accuracy. Producer's accuracy, defined as the probability that a reference plot classified as category i is also classified as category i by the map, is a description of map omission error. Commission error is related to user's accuracy, which is defined as the probability that a pixel classified as category i by the map is also classified as category i by the reference data (Stehman & Czaplewski, 1998). The Kappa statistic is a measure of how well the classification agrees with the reference data, and is based on the difference between the actual agreement in the error matrix and the chance agreement indicated by the error matrix row and column totals. Two tailed t-tests were used for comparing error matrix Kappa statistics to test hypotheses that there were no differences in classifications [H_0: (Kappa−Kappa)=0; $z < 1.96$; $\alpha = 0.05$] (Congalton & Green, 1999). The Kappa statistic, which is dependent on a model-based inference framework, assumes independence of the training and reference data and that the mapped land-cover proportions reproduce the observed map proportions in each class (Stehman, 2000). We were therefore only able to compare producer's and user's accuracies for the Klamath fires since they were sampled using a stratified random scheme.

We compared CBI_R classifications of both the random training and validation sets to the CBI_O classification to determine whether using all plots for training altered the accuracy of the classification reported in Miller and Thode (2007). We also compared the Miller and Thode (2007) classification to a classification using plots restricted to at least 10% pre-fire tree canopy cover to determine whether using only forested plots in the accuracy assessment would affect the CBI_O classification accuracy.

We grouped plots into sets based upon geographic location to test the hypotheses that thresholds developed on one set of fires can be used on other fires in the same geographic region, or in a different region that differs in vegetation structure but supports similar overstory tree species. For PctCC and PctBA classifications, we compared accuracies for both random training and validation sets to: 1) four fires that occurred in the SNFPA area during 2001, and 2) five fires that occurred in the Klamath Mountains during 2006. Since CBI was not measured in the 2001 SNFPA fires, we instead compared the CBI_O classification from Miller and Thode (2007) to seven fires in Yosemite NP as well as the five 2006 Klamath Mountains fires.

Landsat reflectance values can be influenced by a combination of both understory vegetation and overstory trees, especially where tree canopy cover is sparse (Spanner et al., 1990; Stenback & Congalton, 1990). Since the PctCC and PctBA classifications were trained exclusively with tree data, we evaluated how the percentage of pre-fire tree canopy cover affected accuracies. User's and producer's accuracies were compared at incremental levels of pre-fire canopy cover for CBI_O, CBI_R, PctCC and PctBA classifications of the 2002–2004 SNFPA area fires.

3. Results and discussion

3.1. Regression models

Regression models of RdNBR using values for forested plots sampled in the SNFPA area were highly significant for CBI_O, CBI_R, percentage canopy cover change (PctCC), and percentage basal area change (PctBA) (Fig. 4). All data were best fit with nonlinear regression

models and resulted in P values less than 0.0001 (Table 3). Form of the regression models was chosen so that they produced the highest R^2 value and lowest standard error, with the additional requirement that the model must be of a form that can be inverted to allow calculation of RdNBR threshold values.

Regressing CBI to RdNBR with all plots (CBI_R) or a reduced set of randomly selected plots with at least 5% tree cover (CBI_O) produced similar models (Fig. 4A and B), with CBI_R resulting in a higher R^2 value (0.68 and. 0.61, for CBI_R and CBI_O, respectively). Most variables measured in the CBI protocol are relative to the pre-fire condition (Key & Benson, 2005a). If CBI accurately describes the relative change at a location as seen from above by the satellite, the relationship of RdNBR to CBI should also be linear since RdNBR is relative to the pre-fire condition. The plots of RdNBR vs. CBI in Fig. 4A and B displayed a linear relationship for CBI values between approximately 0 and 2, but the slope increased for CBI values greater than 2. Linear regression of CBI to percent change in canopy cover (not shown) indicated that when CBI values were 2.25 or greater at least 95% of the tree canopy was killed ($R^2 = 0.56$, $P < 0.0001$). The increasing slope in the RdNBR–CBI relationship at large CBI values was therefore most likely due to sensitivity of the Landsat TM bands 4 and 7 to soils, ash, char, and substrate materials (Kokaly et al., 2007).

PctCC and PctBA models were almost identical (Fig. 4C and D, and Table 3), which is not surprising since PctCC and PctBA are highly correlated ($r = 0.97$; $P < 0.0001$). Variance in both regression models was fairly large and slope of the model is shallow over most of the range of values which indicates low discriminating power for the dependent variable. In fact, the mean RdNBR for the 0–25% and >75% categories lies within one standard deviation of the 26–75% category mean (Table 4). Mean RdNBR values for the 0–25% and >75% categories were separated by more than one standard deviation (Table 4), which suggests that the regression models should be able to at least discriminate between low and high severity patches. Examining the distribution of RdNBR values in the SNFPA area fires (Fig. 2) a peak was noted at about 250 which corresponds to the mean RdNBR value for the 0–25% change categories. The percentage of pixels then decreased with increasing RdNBR value until reaching an inflection point at about 650 which corresponds to 90% change in canopy cover or basal area as computed with the RdNBR regression models. The PctCC and PctBA regression models indicated that tree mortality was 100% at RdNBR values greater than 750 (Fig. 4), yet pixels continued to vary in value to a maximum of about 1300 (Fig. 2).

3.2. Accuracy assessment

3.2.1. CBI

Accuracies of CBI based classifications were comparable whether training regression models were based on all or a random subset of plots; and accuracies for fires in the SNFPA area, Yosemite NP, and the Klamath Mountains were all similar (Tables 5 and 6). Producer's and user's accuracies for the high severity category improved when plots were constrained to a minimum of 10% pre-fire tree cover. Comparing accuracies reported in Miller and Thode (2007) to those from fires in Yosemite NP (Table 5), the producer's accuracy for the high severity category was similar but user's accuracy for the Yosemite fires was

Table 4
RdNBR statistics and classification thresholds by severity category for the tree based fire severity variables

	Percentage change in canopy cover (PctCC)			Percentage change in basal area (PctBA)		
	0–25%	26–75%	>75%	0–25%	26–75%	>75%
Mean	249	456	799	253	439	798
Standard Deviation	188	216	243	193	207	239
Mean−1 Std. Deviation	61	240	556	60	232	559
Mean+1 Std. Deviation	436	671	1041	446	645	1037
Classification thresholds	0–367	368–572	>572	0–370	371–574	>574

Table 5
Classification accuracies, showing producer's and user's accuracy and Kappa statistics for fires in the SNFPA planning area, Yosemite NP, and the Klamath Mountains

Dataset	Producer's accuracy				User's accuracy				
	Unchanged to low (0–25%)	Moderate (26–75%)	High (>75%)	Unchanged to low (0–25%)	Moderate (26–75%)	High (>75%)	Number of plots	Overall Kappa	Kappa variance
CBI_O									
*SNFPA 2002–2004; all veg types	71.3	53.6	72.1	65.5	58.8	70.4	741	0.464	0.00072
**Yosemite NP; all veg types	88.8	29.8	70.7	55.5	45.2	84.3	273	0.435	0.00162
Klamath Mtns	71.4	46.9	70.7	43.5	50.0	85.3	87	0.413	0.00626
All plots 2002–2004 SNFPA	74.6	55.8	80.2	68.0	63.1	76.2	628	0.527	0.00080
CBI_R									
Training 2002–2004 SNFPA	72.9	59.5	79.1	69.6	63.2	76.8	295	0.521	0.00180
Validation 2002–2004 SNFPA	74.5	60.8	78.1	70.9	63.2	78.1	333	0.552	0.00146
All plots 2002–2004 SNFPA	73.7	60.2	78.5	70.2	63.2	77.6	628	0.539	0.00080
$PctCC$									
Training 2002–2004 SNFPA	73.6	33.8	79.8	74.1	38.1	72.0	295	0.461	0.00176
Validation 2002–2004 SNFPA	72.9	32.4	75.0	73.9	29.6	78.0	346	0.461	0.00140
Validation 2001 SNFPA	78.0	37.7	87.9	62.2	56.9	80.3	252	0.533	0.00185
Klamath Mtns	73.3	37.9	85.7	78.6	52.4	63.2	87		
Klamath Mtns corrected for PCVS	73.9	50.0	82.5	60.7	57.1	86.8	87		
$PctBA$									
Training 2002–2004 SNFPA	72.3	29.6	81.9	72.3	33.9	73.9	295	0.443	0.00179
Validation 2002–2004 SNFPA	73.9	33.8	76.3	70.6	32.9	80.8	346	0.475	0.00139
Validation 2001 SNFPA	73.5	41.5	89.1	66.7	54.0	83.5	252	0.566	0.00178
Klamath Mtns	68.6	29.6	88.0	82.8	40.0	57.9	87		

Note: Accuracies are for plots with at least 10% prefire tree canopy cover, except (*) reproduced from Miller and Thode (2007) and (**) Yosemite NP. CBI_O, CBI_R, PctCC and PctBA are defined in the text.

higher by 14 percentage points (CBI_O in Table 5). The higher user's accuracy may have been due to a higher proportion of tree-dominated plots in the Yosemite fires vs. the plots used by Miller and Thode (97% vs. 91%). For the Klamath fires, producer's accuracy for the CB_O high severity category was lower for all 2002–2004 SNFPA plots with at least 10% pre-fire tree cover, but similar to the accuracy reported by Miller and Thode (2007), and user's accuracy was higher. No difference in Kappa was observed between classifications whether the regression models were trained using all plots (CBI_O) or trained using a random set of plots (CBI_R) (Table 6). There also was no difference between the Kappa for the classification reported in Miller and Thode (2007) and the fires in Yosemite NP.

Except for one of sixteen cases, accuracies for the moderate severity CBI category were always the lowest of the three severity categories in all classifications (Table 5). Although CBI is a linear combination of effects seen in all strata, other researchers have also noted that classification confusion can occur in the moderate severity category, presumably due to complex interactions between those

effects that actually occurred and those that can be observed when viewed from above by the satellite (De Santis & Chuvieco, 2007). The high severity category had the highest accuracies, which is desirable, because areas of high severity fire effects are where the greatest ecological impacts occur and where most post-fire management activities take place. Actual map accuracies are probably higher than those reported in Table 5, for the following reasons: 1) CBI is derived entirely from ocular estimates and variability in observer's estimates could greatly impact accuracy assessment results (Congalton, 1991; Korhonen et al., 2006); and 2) most values estimated in the CBI protocol are relative to pre-fire conditions, which can be difficult to discern since pre-fire conditions are often radically altered by fire (Key, 2006).

3.2.2. Percent change in tree canopy cover and basal area

As with the CBI based classifications, the highest severity category in the PctCC and PctBA classifications had the highest producer's and user's accuracies (Table 5). Producer's and user's accuracies for the

Table 6
Classification comparisons for three severity measures using a *t*-test of Kappa statistics between training plots and validation plots

Dataset	CBI_O: SNFPA area 2002–2004; all veg types	CBI_R: training 2002–2004	PctCC: training 2002–2004	PctCC: validation 2002–2004	PctBA: training 2002–2004	PctBA: validation 2002–2004
CBI_O						
Yosemite NP	0.60					
2002–2004 SNFPA; >10% tree cover	1.62					
CBI_R						
Training 2002–2004 SNFPA	0.12					
Validation 2002–2004 SNFPA	0.53	0.54				
All plots 2002–2004 SNFPA	0.30					
$PctCC$						
Validation 2002–2004 SNFPA			0.00			
Validation 2001 SNFPA			1.20	1.26		
$PctBA$						
Validation 2002–2004 NFPA					0.57	
Validation 2001 SNFPA					*2.06	1.62

Note: All null hypotheses are accepted except (*) H_0: ($Kappa_{row} - Kappa_{column}$)=0; $z < 1.96$; $\alpha = 0.05$.

high severity category ranged between 72.0% and 89.1%, with the exception of the Klamath fires where accuracies were 63.2% and 57.9%, respectively. The moderate category of 26–75% change had the lowest accuracies; lower than the moderate severity category of the CBI maps, and not much better than would be expected by a random classification. The low accuracy of the 26–75% category is probably due to a combination of factors: 1) "moderate" severity fire is by nature a composite of high and low severity fire effects where neither clearly dominates; 2) high spatial variability in the distribution of moderate fire patterns, 3) structural variability in over- and understory cover, and 4) moderate severity effects are often mapped as narrow bands surrounding areas of high severity. The first derivative of RdNBR, shown in Fig. 5 for a typical fire with distinct high severity patches, demonstrates how the moderate severity category often occurs in narrow bands of 1 or 2 pixels width around patches of high severity. As a result, moderate severity fire effects often occur at a scale that is finer than 30 m pixels can be homogeneously categorized; the resulting "mixed pixels" are a major source of errors in hard (as opposed to fuzzy) classifications (Congalton & Green, 1999).

There are several possible reasons for the low (63.2% and 57.9%) user's accuracy of the >75% category for the Klamath PctCC and PctBA classifications (Table 5). As noted in the methods section, plot selection in the Klamath Mountains emphasized sampling areas exhibiting effects in the upper moderate category and lower high severity category. In some of these moderate to high severity areas, the tallest trees with largest diameters were the only trees that retained any green canopy. Total plot basal area was highly skewed by the large diameter trees and therefore the loss in basal area in these plots was low relative to the loss of leaf area. Because we over sampled plots falling near the moderate-high severity boundary, the proportion of plots exhibiting this characteristic likely over-represented the actual area affected by this level of fire severity, consequently disproportionately lowering the user's accuracy. Post-fire canopy cover estimates were also affected because FVS calculations of canopy

cover do not account for loss of canopy due to scorch (Crookston & Stage, 1999). This issue is discussed in more detail in the next section of this paper.

Although PctCC and PctBA producer's accuracies for the 2001 SNFPA fires were about 13 percentage points higher than the random validation sets, there was no statistical difference in the Kappa statistic. The 2001 SNFPA PctBA Kappa statistic was significantly different from the 2002–2004 training classification (Table 6), with user's and producer's accuracies for the 2001 validation classification higher than the training classification (Table 5). The 2001 PctBA validation classification Kappa statistic was not different from the 2002–2004 validation classification however, nor was the 2001 PctCC classification different from either the PctCC training or 2002–2004 validation classification (Table 6). Examining the distribution of plots sampled in each category, the 2001 SNFPA fires had higher proportion of plots in the >75% category than did the 2002–2004 fires (48% and 34%, respectively) which may have affected the Kappa statistic comparison.

3.2.3. Effects of sampling protocols and FVS calculations on accuracies

We found that classification errors for canopy cover and basal area change could be traced both to our sampling protocol and to our use of FVS to calculate canopy cover. For example, we measured trees in subplots for the SNFPA fires, but examination of photos of misclassified plots with low pre-fire tree density showed that in some cases the use of subplots caused trees to be either over or under sampled. Second, in SNFPA fires, post-fire basal area was overestimated for hardwood tree species that were top killed and then sprouted post-fire. Pre-fire basal area was used in calculating post-fire basal area and cover instead of using the basal area of the post-fire resprouts. Third, calculating canopy cover with FVS may have underestimated canopy cover change. Given that FVS uses empirically derived models of canopy cover based on species and tree diameter, there was no method to account for reduction in crown width due to canopy scorch. For example, nine plots measured in the Klamath fires had average crown scorch heights that were 90 to 95% of maximum tree height. With this amount of crown scorch, width of the remaining living crown and therefore canopy cover was likely substantially smaller than values calculated with FVS. This is one probable reason for the low user's accuracies in the >75% change category (Table 5). When we calculated a canopy cover change correction using the actual (0–100%) "percent scorched" measurement for overstory trees recorded on the CBI data form as an estimate of PCVS (Fig. 3), we observed a substantial increase in user's accuracy for the >75% category (from 63.2 to 86.8%; Table 5). It should be noted that these errors in deriving field reference values not only affect the error matrices for the Klamath fires, but also the variance in the SNFPA fire data. As a result, the PctCC producer's accuracies we reported for SNFPA fires are probably understated. We could not evaluate how the correction would affect accuracies for SNFPA fires however, since we did not record the percentage of crown volume scorched for all SNFPA area plots. Note that the reduction in Klamath fires user's accuracy for the <25% category that occurred when applying the canopy cover change correction may not be realistic. The equations we used to model canopy shape assume that tree canopies are always widest at the base of the canopy. If on the other hand, tree canopies are wider in diameter several meters above the base (Gersonde et al., 2004), low levels of crown scorch would result in no reduction in canopy cover.

3.2.4. Accuracy as a function of pre-fire tree canopy cover

Mapping vegetation with sparse cover has historically been a remote sensing challenge since wavelengths used for the detection of vegetation are also influenced by the amount of exposed soil, parent substrate, soil water content, and in the case of fire, post-fire ash cover (Huete, 1988; Rogan & Yool, 2001; Kokaly et al., 2007). With respect to estimating CBI values with satellite derived indices, Chuvieco et al. (2006) also found that variations in soil and leaf chlorophyll when pre-fire cover was low caused higher noise levels, making it difficult to
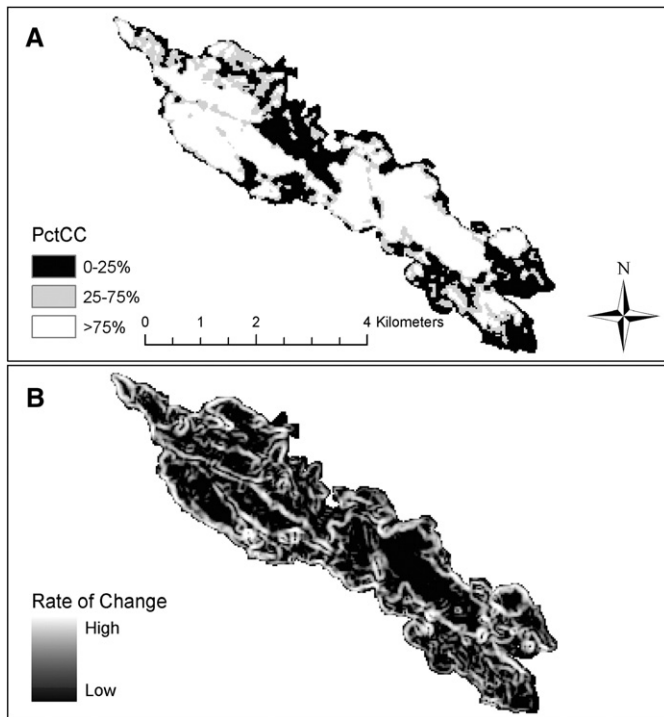
Fig. 5. A typical fire with distinct high severity patches demonstrating how the moderate severity category often occurs in narrow bands of rapid transition between high and low severities. (A) Percent change in tree canopy cover classification. (B) The first derivative of RdNBR, lighter areas indicates a greater rate of change.

Table 7
Producer's and user's accuracy for different fire severity measures as a function of pre-fire tree canopy cover in SNFPA area plots

Variable	% Pre-fire tree cover	Producer's accuracy			User's accuracy		
		Unchanged to low (0–25%)	Moderate (26–75%)	High (>75%)	Unchanged to low (0–25%)	Moderate (26–75%)	High (>75%)
CBI$_O$	1–10	43.5	55.0	83.3	83.3	52.4	45.5
	10–20	68.0	59.1	47.4	85.0	43.3	56.3
	20–40	71.2	56.8	85.7	78.7	58.1	73.2
	40–60	67.3	62.1	84.6	70.0	62.1	80.5
	60–80	88.2	52.7	87.8	63.4	76.5	82.7
	80–100	76.0	50.9	76.7	51.4	67.5	74.2
CBI$_R$	1–10	43.5	60.0	83.3	83.3	54.5	47.6
	10–20	68.0	59.1	47.4	85.0	43.3	56.3
	20–40	71.2	63.6	85.7	82.2	60.9	75.0
	40–60	63.5	65.5	79.5	70.2	58.5	83.8
	60–80	88.2	56.8	85.7	65.2	76.4	84.0
	80–100	76.0	56.6	76.7	55.9	69.8	74.2
PctCC	1–10	36.4	66.7	60.5	66.7	9.5	76.7
	10–20	75.0	12.5	57.1	81.1	4.8	80.0
	20–40	66.2	29.4	79.7	72.9	27.8	74.3
	40–60	78.3	41.9	86.0	73.9	46.4	85.1
	60–80	76.7	33.3	84.8	69.0	46.3	76.4
	80–100	73.5	34.9	81.4	64.3	53.6	68.6
PctBA	1–10	36.4	66.7	57.9	66.7	9.1	75.9
	10–20	73.8	20.0	55.6	83.8	4.8	80.0
	20–40	67.5	31.0	80.9	77.8	25.7	75.3
	40–60	69.7	40.9	87.5	77.5	32.7	88.5
	60–80	77.3	35.9	87.8	68.0	51.9	78.2
	80–100	87.1	31.6	83.0	47.4	66.7	76.5

estimate CBI. Satellite reflectance values are primarily correlated to variables associated with the tree canopy in forested environments. When tree canopy cover is sparse, satellite reflectance values are influenced by a combination of both understory vegetation and overstory trees (Spanner et al., 1990; Stenback & Congalton, 1990). Conifer forest types in the Klamath Mountains and SNFPA area rarely experience running crown fire and therefore when overstory trees experience high severity fire effects, understory plants typically do also. However, the inverse situation where only understory plants experience high severity fire while leaving the overstory trees mostly intact also often occurs (Sugihara et al., 2006). When shrub density is high and trees are sparse, high severity fire effects to shrubs can overwhelm a low severity overstory signal. PctCC and PctBA are both measures of tree canopy; therefore accuracies for those variables should be highest when tree cover is high. But severity may be over estimated when tree density is low and understory vegetation has experienced high severity fire. CBI on the other hand is a measure of fire effects across all vertical vegetation strata and accuracies should be higher than PctCC and PctBA when tree density is low.

Examining accuracies with regard to pre-fire tree canopy cover revealed mostly intuitive patterns (Table 7). Producer's accuracies for the high severity category, regardless of field severity measure, were almost always higher when pre-fire tree canopy cover was at least 20%. The decrease in user's accuracy for >75% PctCC category when pre-fire canopy cover was high is most likely due to overestimation of post-fire tree cover. This is because FVS cannot internally estimate change in canopy width due to crown scorch (see above), but also because canopy cover can be overestimated when tree density is high, because FVS assumes that the complete crown area is included inside the plot boundary (Crookston & Stage, 1999). User's accuracies of the 26–75% PctCC and PctBA categories were very poor when pre-fire tree cover was low, but accuracy increased as pre-fire tree cover increased to about the average level of the moderate CBI category. This was probably due to plots with few large trees containing more shrubs and small trees; in these cases change as detected by satellite can be disproportionately high, even with a low-intensity fire that does not affect the crowns of the larger trees. Conversely, user's accuracies for the 0–25% change category decreased as pre-fire tree cover increased, most likely due to trees in the upper canopy obscuring the satellite's view of mid-story trees that are more likely to be affected by lower severity fire. User's accuracies of the moderate CBI category also increased with increasing pre-fire tree cover, although at a much lower rate. Producer's accuracies of the moderate severity CBI category consistently averaged between 50 and 60% regardless of pre-fire tree cover. CBI is a composite measurement of severity accounting for all vegetation strata, whereas change in canopy cover and basal area are only a measure of trees. Because the satellite index is highly sensitive to chlorophyll and is integrated over both horizontal and vertical space, CBI values more closely represent what is measured by the satellite, except where post-fire live tree canopy is dense enough to obstruct the view of the understory.

4. Conclusions

In this paper we demonstrate that the relative index methodology and CBI regression model presented in Miller and Thode (2007) can produce classifications that are of similar accuracy in fires not used in the original calibration process, at least in conifer dominated vegetation types in Mediterranean–climate California. Models trained with randomly selected plots also produced classifications with accuracies similar to the results originally reported in Miller and Thode (2007). We see no evidence at this time that would preclude use of the models presented here for mapping patches of high severity fire in conifer dominated vegetation types similar to those that occur in the SNFPA area and Klamath Mountains, whether defined by CBI, percent change in tree canopy cover or basal area. Accuracies of the high severity categories across all classifications ranged between 70.7% and 89.1%, which are consistent with those reported by other researchers (Cocke et al., 2005; Epting et al., 2005; Stow et al., 2007). Accuracies also tended to increase as a function of increasing pre-fire tree cover. Classification accuracies for the SNFPA fires are unlikely to have been overestimated because the distribution of RdNBR values at field plot locations was similar to the overall distribution of RdNBR values in those fires. Indeed, there is evidence that all our classification accuracies may be understated because: 1) the ground measure itself, CBI, contains variation that is unaccounted for due to reliance on ocular estimates; 2) FVS canopy cover estimates do not account for percent of crown volume scorched; 3) other studies have shown that variability in FVS tree canopy cover estimates can be high; 4) basal

area estimates in the SNFPA fires did not account for reduction in basal area of sprouting hardwood species; and 5) trees may have been over or under sampled in plots with low pre-fire tree density in the SNFPA fires.

Our modeling of the relationship of RdNBR to percent change in canopy cover and basal area resulted in similar regression models. There are difficulties with mapping either variable. We acknowledge that modeling canopy cover using tree inventory data may not be the most precise method, but we used established methods and when combining data from multiple fires our sample size should have allowed for sufficient accuracy in our regression model. In contrast basal area depends on the relationship of tree diameter to canopy width which is modified by fire, but the wavelengths recorded by the satellite and used in the NBR index are more directly related to the canopy, not dbh. Our results however, will allow land managers to better understand how both of these variables relate to maps of severity derived from satellite imagery.

Passive remote sensing of fire effects to individual strata in forested environments is difficult due to the complex combination of effects integrated over vertical and horizontal space. The low accuracy of the 26–75% change category for the PctCC and PctBA classifications demonstrates the difficulty in separating out those effects. More sophisticated analysis techniques, such as spectral mixture analysis (SMA), may be more successful (Rogan & Franklin, 2001; Lu et al., 2005). Detailed mapping of individual severity effects using SMA techniques on hundreds of fires, however, would require time and expertise not available to many organizations, and development of automated SMA techniques for discriminating effects to individual forest strata has not yet occurred. Our analyses show that maps of percent change in tree canopy cover or basal area produced with the methods presented here can be used with reasonable accuracy to identify and analyze patches of high fire severity (>75% change). On the other hand, accuracies of the moderate (26–75%) change categories were much lower, warranting greater scrutiny and caution in application. The CBI classification resulted in higher accuracies for the moderate category, but is probably best used with the understanding that the total plot CBI used in this study is an aggregate of fire effects across all strata, and not uniquely descriptive of effects to any single stratum.

Acknowledgements

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